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When Object Color is a Red Herring: Extraneous Perceptual Information Hinders Word Learning via Referent Selection

Jessica S. Horst, Katherine E. Twomey, Anthony F. Morse, Rosie Nurse, and Angelo Cangelosi

Abstract—Learning words from ambiguous naming events is difficult. In such situations, children struggle with not attending to task irrelevant information when learning object names. The current study reduces the problem space of learning names for object categories by holding color constant between the target and other extraneous objects. We examine how this influences two types of word learning (retention and generalization) in both 30-month-old children (Experiment 1) and the iCub humanoid robot (Experiment 2). Overall, all children and iCub performed well on the retention trials, but they were only able to generalize the novel names to new exemplars of the target categories if the objects were originally encountered in sets with objects of the same colors, not if the objects were originally encountered in sets with objects of different colors. These data demonstrate that less information presented during the learning phase narrows the problem space and leads to better word learning success for both children and iCub. Findings are discussed in terms of cognitive load and desirable difficulties.

Index Terms—Desirable Difficulties, Extraneous Information, Garner Interference, Modeling, Word Learning

I. INTRODUCTION

THE world is a busy, colorful place. When children learn names for things in their world (i.e., object categories), they do not do so in isolation; background noise interferes with the message [1], the visual scene is cluttered [2, 3], and other things may be present that are irrelevant to the task at hand [4, 5]. In addition, when a child hears a name during an ambiguous naming event, there are arguably infinite possible referents to a new word. Fortunately, children quickly learn regularities from their input and environment that help them reduce the problem space, by taking advantage of a variety of sources of information, for example their known vocabulary [6, 7], input from social partners [8], pragmatic information [9], and temporal contiguity [10].

It is vital to reduce the problem space when learning words from ambiguous naming events because children are also learning what new words *do not* refer to [11]. Several studies demonstrate how extraneous, additional objects present during naming events hinder word learning. For example, when there are more than two extraneous objects present on referent selection trials, 30-month-old children fail to learn words even with feedback [3]. Similarly, children struggle to learn words when objects are named in multiple, unpredictable locations [12] and when extraneous objects are relatively large in the visual field relative to target objects [13]. Thus, extraneous objects make word learning from ambiguous naming events difficult.

The current study aims to reduce the problem space of learning names for object categories from ambiguous naming events by holding objects' colors constant. Members of real-world object categories often share both shape and color, but shape is the feature that determines category membership [14, 15], while color remains an attribute [16]. Critically, once children have learned to produce 50 nouns they reliably demonstrate the "shape bias" [17]. That is, like adults, children generalize the name for an object to other members from the same category on the basis of shape. However, children still have difficulty in not attending to extraneous objects and in ignoring task irrelevant information. For example, when children hear a familiar word, they will look at that referent but they also look at visually similar competitors [18]. Indeed, adults also struggle to ignore color even when explicitly told to attend to objects' shapes [19]. Extraneous information like objects' color captures attention, which in turn prevents children from processing task relevant information [20], which in the case of object name learning is the objects' shapes. This suggests, then, that decreasing task irrelevant information about competitor objects (color), should improve children's ability to process task relevant information (shape), and in turn improve word learning.

To further understand how irrelevant information hinders word learning from ambiguous naming events we examined

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this learning both empirically (Experiment 1) and computationally (Experiment 2). We tested 30-month-old children to maintain continuity with previous studies [3, 21] and because children at this age are unlikely to know many color terms [22, 23] but already know to extend object names on the basis of shape [24, 25]. Children were taught names for four novel object categories via referent selection trials (disambiguation trials on which they chose one referent of a given word from among several possible objects). In the same colors conditions, all objects present during the naming events shared the same color. In the different colors conditions, all objects present during the naming events were different colors. That is, color was either constant or variable. We tested two forms of word learning: retention (recalling the original name-object associations after a delay in a new context) and generalization (extending the names to new category members, specifically exemplars of the same shape but different colors). If children encounter sets of objects that are all the same color and only vary in shape they should have less difficulty attending to and encoding the task relevant information (shape). However, if children encounter sets of objects that vary in both color and shape they should have more difficulty attending to and encoding the task relevant information. Put another way, if all of the objects are the same color that reduces the local salience of the redundant attribute (color) and hence increases the local salience of the relevant attribute (shape). Consequently, children who encounter objects of the same color should learn more words than children who attend to both the irrelevant and relevant attributes.

For our computational approach we present the same word learning task to the iCub robot [26] using a version of the Epigenetic Robotics Architecture, ERA [27], which processes both objects' shapes and colors. This architecture allows us to examine generalization without adding an additional input layer ad hoc. Other models of word learning [e.g., 11], do not have this built-in capability because the input layers consist of localist units without any associated shape or color information (but see [28]). In addition, iCub affords unprecedented task veridicality as both iCub and children can be given the same 3D objects and perform the same overt reaching behaviors (see Figure 1). Thus, iCub is an ideal platform to provide theoretical insights into how reducing the problem space during referent selection influences child word learning. Furthermore the same model has replicated numerous other experiments, including children's ability to solve disambiguation trials with what appears to be a mutual exclusivity principle as well as children's novelty bias [29]. These findings indicate that task effects and embodiment influence the behavior of iCub and children in similar ways. If our hypotheses of how children are processing the shape and color input are correct, then iCub should behave like children when presented with the same objects in the same task. By using the same model with iCub across multiple developmental stages, in ongoing learning and

interaction and without parameter changes [30], we can demonstrate an integrated account of language acquisition.

II. EXPERIMENT 1

A. Method

1) Participants

Thirty-six typically-developing 30-month-old children participated ($M = 30.38$ months, $SD = 53.83$ days, range = 27.58-33.84 months). Children were randomly assigned to either the same colors or different colors condition. None of the children had any family history of colorblindness. The majority of children were from White, middle-class families. Children in the two conditions did not differ in age (same colors: $M_{age} = 30.44$ months, $SD = 51.53$ days, range = 28.01-33.84 months,

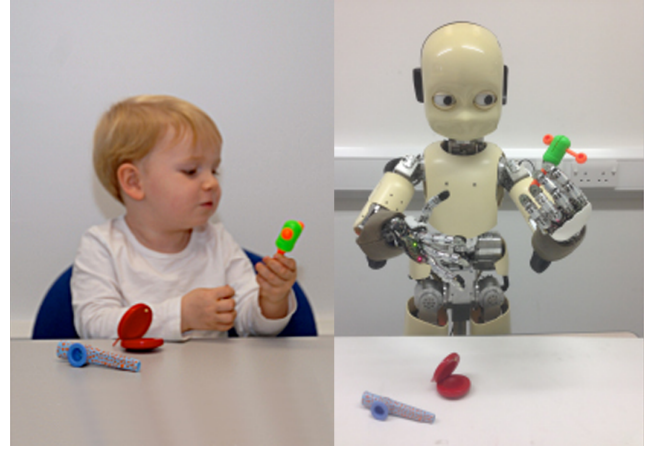


Fig. 1. A child (left, Experiment 1) and iCub (right, Experiment 2) completed the same trials.

six girls; different colors: $M_{age} = 30.32$ months, $SD = 57.48$ days, range = 27.58-33.51 months, eight girls; $t(34) = 0.21$, $p = .83$, $d = .06$) or productive vocabulary (same colors: $M_{vocab} = 576.89$ words, $SD = 126.34$ words, range = 178-663; different colors: $M_{vocab} = 515.22$ words, $SD = 171.60$ words, range = 174-666; $t(34) = 1.23$, $p = .23$, $d = .42$). One additional child in the same colors condition did not complete the task. Parents were reimbursed for travel expenses and children received a small gift for participating.

2) Stimuli

The same stimuli were presented to children in Experiment 1 and to iCub in Experiment 2. Different objects were used across the different trial types and are described in turn, below. All objects were similar in size (approximately 4.00cm x 6.91cm x 4.82cm).

1) *Warm-up stimuli.* Six known objects served as stimuli on the warm-up trials: two blocks (one green, one purple), two fish (one green, one orange) and two motorcycles (one green, one black). Children in the same colors condition saw the three green objects. These objects were originally green when purchased, but were painted in the lab to ensure they were the exact same shade of green. Children in the different colors condition saw the other objects. These objects were not painted because there were no other objects that shared the same colors (purple, orange, black).

TABLE I
STIMULI

	Same color sets			Different color sets		
Warm-up	Motorcycle (green)	Fish (green)	Block (green)	Motorcycle (black)	Fish (green)	Block (purple)
<i>Cheem</i>	Kazoo (red)	Ladybug (red)	Bus (red)	Kazoo (red)	Glasses (blue)	Cup (pink)
<i>Doff</i>	Castanet (blue)	Glasses (blue)	Boat (blue)	Castanet (blue)	Train (yellow)	Pig (pink)
<i>Gaz</i>	Clacker (pink)	Pig (pink)	Cup (pink)	Clacker (pink)	Lion (yellow)	Bus (red)
<i>Hux</i>	Noisemaker (yellow)	Train (yellow)	Lion (yellow)	Noisemaker (yellow)	Ladybug (red)	Boat (blue)

In both conditions, children and iCub saw the same known and novel objects during the referent selection phase. For the same colors condition sets were assembled so that all objects within each set were the same color as each other. For the different colors condition sets were assembled so that all of the objects within each set were different colors to each other. Across trials all children and iCub simulations encountered the same objects the same number of times.

2) *Referent selection and retention stimuli.* The same referent selection and retention stimuli were used for both conditions. Four novel, unfamiliar toys served as target stimuli: a red, plastic kazoo (*cheem*), a blue, wooden castanet (*doff*), a pink, plastic butterfly clacker (*gaz*) and a yellow noisemaker (*hux*). Word-object pairs were held constant to minimize experimenter error [31]. Importantly, the novel objects were chosen to be sufficiently novel to children that the categories would not be associated with a canonical color, that is, the color was arbitrary. Eight known objects also served as stimuli: a boat, a bus, a cup, a pair of glasses, a ladybug, a lion, a pig and a train. These categories were chosen because their names are typically known by 30-month-old children, according to Macarthur-Bates Communicative Development Inventory acquisition norms [32].

Objects were presented in sets of one novel and two known objects. Sets were created so that all objects in a set were from different global categories (e.g., no sets contained multiple animals), because the perceptual similarity between items presented together can interfere with young children's processing of global categories [33]. Every object used during the referent selection and retention trials was painted so that the sets in the same colors condition were the exact same color. For example, one set included the red kazoo, the red ladybug and the red bus (see Table 1). Note, where familiar objects had a canonical color (e.g., red ladybug) they maintained that color (which should not facilitate processing, but if violated could interfere with processing and object recognition [16, 18, 34]).

3) *Generalization stimuli.* The same generalization stimuli were used for both conditions. New exemplars from the same novel, unfamiliar toy categories served as target stimuli on the generalization trials: a blue, plastic kazoo with orange dots (*cheem*), a red, wooden castanet with painted rings on the lid (*doff*), a green, plastic butterfly clacker with yellow arms (*gaz*) and an orange noisemaker with green center (*hux*). These objects were not re-painted, that is, they were their original colors from the manufacturers, except for the orange dots on the kazoo, which had been added previously for a different study [21].

3) Design

During the referent selection phase every child saw the exact same objects and saw them the same same number of times. The

critical—and only—difference between conditions was whether the objects that were presented together on each referent selection trial were all the same color or all different colors (see Table 1). In the same colors condition, the objects were always the same color as each other on any given trial (i.e., color constancy within sets). For example, the red kazoo was paired with the red ladybug and the red bus and the pink clacker with the pink pig and pink cup. In the different colors condition, the objects were never the same color as each other on any given trial (cf. [3, 21, 35-38]). For example, the red kazoo was paired with the pink cup and blue glasses and the pink clacker with the yellow lion and red bus. This ensured that children in both conditions saw the exact same stimuli.

Each set was presented twice: once for a novel name trial (e.g., *cheem*) and once for a known name trial (e.g., *bus*). Known name trials were included to ensure that children were listening to what the experimenter requested and not always choosing the novel object (see also, [39, 40]). The order of known and novel trials was pseudo-randomized such that the same set was never presented on two consecutive trials and no more than two trials of either type (i.e., known or novel) were presented sequentially. In addition, trial order and set order were counterbalanced across children. Object locations were randomly determined on each trial. Critically, children in both conditions saw each object the same number of times across referent selection, retention and generalization trials. All children saw the same stimuli on the generalization trials.

4) Procedure

The experiment began with three warm-up trials to introduce the child to the task. The experimenter sat opposite the child at a light gray table. The parent sat next to the child and completed a vocabulary checklist [41]. On each warm-up trial the experimenter presented three objects on a clear Plexiglas tray, that was evenly divided into three sections. The experimenter set the tray of objects on the table and silently counted for three seconds to provide the child with an opportunity to look at the objects (see [35]). The experimenter then asked the child to select an object by naming it five times (e.g., "Can you get the fish? Which one is the fish? Where is the fish? Can you find the fish? Get the fish!") before sliding the tray forward. Each object was requested once and served as a competitor on the other trials. Between trials the experimenter replaced the tray on her

lap and arranged the objects for the next trial out of the child's view. Thus, object locations (left, middle, right) were pseudo-randomized across trials, to ensure the child practiced choosing an item at each possible location. Children were praised or corrected after each trial. Then, the experimenter provided explicit feedback (cf. ostensive naming; [3, 35]). The experimenter slid the tray of objects back to its starting point, picked up the target, pointed to it and named it, for example, "Look, this is the fish!" Warm-up trials were consistent with condition: in the same colors condition the objects were the same color, and in the different colors condition the objects were different colors.

1) *Referent selection.* Referent selection trials immediately followed the warm-up trials using the same procedure except that children did not receive any praise or correction, but they did receive explicit feedback as young children cannot retain names learned on only a single disambiguation trial without such feedback [3, 42]. The experimenter always held up and named the target object, even if the child chose incorrectly, so that the procedure was the same on every trial.

After the referent selection trials, there was a 5-minute delay during which the child played in the laboratory waiting room. This filled delay ensured that children's responses on later trials were not driven by working memory (for a similar argument see [35]). None of the objects used in the experiment, known or novel, were present in the waiting room.

2) *Retention and generalization.* The retention and generalization tasks were the same in both conditions. First, to re-engage the child in the task, a re-engagement trial with the warm-up trial stimuli was presented. This was immediately followed by four retention trials, where three novel objects seen during referent selection were presented per trial. On these trials, the experimenter asked the child to select an object, naming it twice (e.g., "Can you find the *cheem*? Get the *cheem*!"). Each object was requested once and served as a competitor on two other retention trials, thus each object was seen exactly three times. In addition, by counterbalancing across children, a third of the children were asked for the kazoo with the castanet and clacker present, a third were asked with the clacker and noisemaker present and a third were asked with the castanet and noisemaker present. Children did not receive any feedback on the retention trials.

Four generalization trials immediately followed using the same procedure with the new exemplars from the original novel object categories: blue kazoo, red castanet, green clacker and orange noisemaker. The counterbalancing was the same as on the retention trials. Children did not receive any feedback on the generalization trials.

Critically, because retention and generalization trials included no known objects, correct responding reflected the children's robust name-object associations [29]. Retention trials tested their memory of just-formed associations, and generalization trials tested whether these associations could be extended to new exemplars from the same object categories.

3) *Coding.* Children's responses were coded online by the experimenter. A naïve coder coded 20% of the sessions from video footage. Inter-coder reliability was 100%. As in previous studies, (e.g., [35, 43, 44]) only the words that children correctly selected during the referent selection trials were included in the analyses of the child's retention. Similarly, only

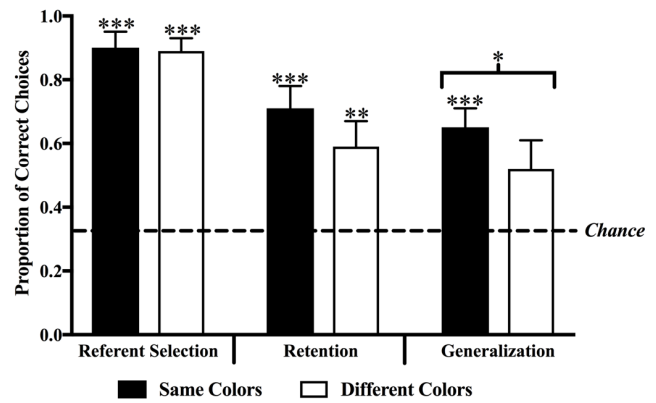


Fig 2. Data from the children. Dark bars indicate the same colors condition, white bars indicate different colors condition. Dotted line indicates level of chance performance. *** $p < .001$, ** $p < .01$, * $p < .05$. Error bars represent one standard error of the mean.

words that children correctly retained were included in the analyses of the child's generalization.

B. Results and Discussion

Results are depicted in Figure 2. As can be clearly seen, children in both conditions chose the target objects significantly more than expected by chance (.33) on the novel name referent selection trials (all t -tests two-tailed; same colors: $M = .90$, $SE = .05$, $t(17) = 11.38$, $p < .001$, $d = 2.70$; different colors: $M = .89$, $SE = .04$, $t(17) = 15.32$, $p < .001$, $d = 3.63$). There was no difference in referent selection performance between conditions, $t(30.99) = 0.22$, $p = .82$, $d = .06$, which is not surprising as numerous studies have documented that young children are highly skilled at mapping novel names to novel objects in such tasks (e.g., [35, 38, 45]).

Our main questions in this experiment were whether color constancy, as opposed to color variability, would facilitate retention and generalization. As can be seen in Figure 2, children in both conditions chose the target objects significantly more than expected by chance (.33) on the retention trials (same colors: $M = .71$, $SE = .07$, $t(17) = 11.38$, $p < .001$, $d = 2.70$; different colors: $M = .59$, $SE = .08$, $t(17) = 15.32$, $p < .001$, $d = 3.63$). There was no difference in retention performance between conditions, $t(33.58) = 1.11$, $p = .28$, $d = .34$, two-tailed. These data are important because the standard method for administering referent selection trials is to present objects that are different colors to each other (e.g., [3, 37, 46-49]). By demonstrating that children in the different colors condition were able to retain the novel name-object associations introduced via referent selection with ostensive naming, we have successfully replicated previous studies (e.g., [3]).

However, only children in the same colors condition were able to generalize the novel names to new exemplars from the target categories (see Figure 2, right-most columns). Children in the same colors condition chose the target objects significantly more than expected by chance (.33) on the generalization trials ($M = .75$, $SE = .08$, $t(17) = 5.63$, $p < .001$, $d = 1.32$), but children in the different colors condition did not ($M = .49$, $SE = .10$, $t(17) = 1.65$, $p = .11$, $d = 0.39$). Moreover,

children in the same colors condition generalized more novel names to new exemplars than children in the different colors condition ($t(31.86) = 2.12, p = .04, d = 0.71$). Taken together, these data clearly demonstrate that reducing the problem space during referent selection facilitates a fundamental component of word learning: children’s word generalization.

III. EXPERIMENT 2

Models of early language learning have demonstrated that apparently complex phenomena can be accounted for by simple low-level associative or probabilistic processes (e.g., [11, 29, 50-53]). However, to render a model of a cognitive process feasible in terms of computational and engineering resources, many aspects of the biological target must be left out of the model. These simplifications force modelers to explicitly specify the cognitive mechanisms they assume to be driving development, noting which mechanisms are essential to reproduce the behavior of interest, and which can be discarded [54]. As such, models require a principled implementation of the learning environment: if a model is to tell us something about development, it should be able to behave similarly to children, given input that resembles the input to children. Thus, the environmental variables which affect children’s word learning should have the same effect on a model’s learning.

A. The iCub and the Epigenetic Robotics Architecture

iCub is specifically designed to investigate early embodied cognitive development (for a review, see [54]). iCub has successfully replicated children’s ability to respond to disambiguation trials as if using a mutual exclusivity principle [55] as well as children’s novelty bias [29]. Its body morphology and stature reflect that of a toddler, with 53 degrees of freedom in the neck, eyes, arms, hands, legs and torso. As well as haptic and proprioceptive feedback from its actuators iCub receives visual information from its cameras and auditory information from its microphones. Thus, like children, iCub integrates a range of perceptual and sensorimotor inputs when generating a behavior, although which of these sources of information serves as input in a particular implementation are determined by the researcher in advance.

As in previous studies we employed the Epigenetic Robotics Architecture (ERA; [27]) as the cognitive architecture in the current simulation. The current architecture is depicted in Figure 3, and consists of visual, posture, and action Self-Organizing Maps (SOMs; [56]) and a connectionist label field, linked bidirectionally via Hebbian-like connections. SOMs are biologically-motivated connectionist neural networks that restructure their internal organization in response to external input. During learning the structure of the map changes such that neurons sensitive to perceptually similar items move closer together. Thus, after learning, a neuron that fires in response to the color red will be situated close to a neuron that fires in response to the color pink, but distant from a neuron that fires in response to the color blue.

Visual input consists of video from iCub’s cameras, fed to two SOMs, which process color and shape information. The color map receives HSV (hue, saturation, value; [57]) spectral values. For each object, the location in HSV color space of each

pixel is determined. Background information (i.e., the white tabletop) and pixels with a saturation value lower than 0.2 are discarded. The remaining pixels are assumed to represent the object, and are assigned to 10-degree bins along the 360 degree

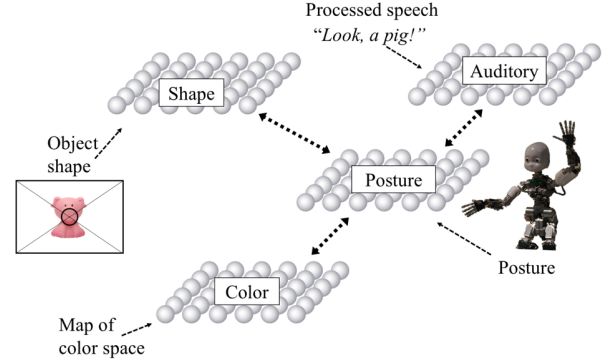


Fig. 3. Schematic of the Epigenetic Robotics Architecture

HSV color continuum. This method generates a unique, cumulative color profile for each object. Thus, the model differentiates between uniformly colored and multicolored objects. The shape map receives geometric information, for example circleness, squareness, convexity and elongation [58]. Again, this generates a unique shape profile for each object; for example, while a toy bus shares a shape profile with the same bus when laid down, a toy boat would generate a different profile.

The posture map receives proprioceptive information from iCub’s limbs and torso, while the action field determines where the iCub looks, reaches and points, thus the color and shape fields tell us “what” something is, and the posture and action fields tell us “where” it is. Finally, individual nodes in the label field receive discrete input for individual object labels. Label input is provided via the commercial software Dragon Dictate™, which uses speech recognition to generate text input.

Overall, the ERA can be viewed as a spreading activation network in which activation flows between SOMs via the label and posture units, subject to excitation and inhibition. When an object appears in iCub’s visual field, the corresponding representation (distributed across the SOMs) is activated. In turn, one or more nodes become activated in the label field, corresponding to children’s retrieval of lexical items in response to visual stimuli. In the current simulation, inspecting the match (or mismatch) between label and object provides a proxy for children’s responses on test trials. While variation in learning rates strengthens/weakens the global patterns of behavior, it is robust to these parameter changes in terms of group differences. Details of the current parameters are provided in the Appendix.

B. Method

1) Stimuli

The same stimuli as in Experiment 1 were used.

2) Design

The same design as in Experiment 1 was used except that iCub did not require warm-up trials, re-engagement trials or a delay

(see [29] for a similar method). Counterbalancing and trial order were identical for Experiments 1 and 2.

3) Vocabulary pre-testing

Children come to the lab with an existing vocabulary, which influences their behavior in referent selection trials (e.g., [45]). We simulated this knowledge by pre-training iCub with the names for the eight known object categories from Experiment 1. During vocabulary pre-training, a single object was placed in the center of the robot’s visual field on a white surface, and the SOMs were allowed to settle (i.e., form a stable representation of the object). Then, iCub was provided with the object label 20 times, sufficient for the object to be robustly associated with its label. This process was repeated for all eight known object categories. Clearly, iCub’s pre-trained vocabulary is substantially smaller than 30-month-old children’s vocabularies. In line with the abstractions typical in computational modeling this simplification was made to render the simulation feasible. Thus, iCub, like children, began the experiment with a vocabulary of known words.

4) Experimental Procedure

We ran the robot task 18 times in each condition with SOM and label field weights initialized randomly. Each time we tested iCub, the robot completed eight referent selection trials (four novel name, four known name), four retention trials and then four generalization trials.

1) *Referent selection.* The experiment followed the same procedure as Twomey and colleagues’ [29] iCub replication of Horst, Scott and Pollard [3]. On each trial the experimenter placed a set of objects in the robot’s visual field with object position (left/center/right) pseudo-randomized across trials. A large piece of glass was used in place of the Plexiglas tray used with children. As in the pre-training phase, once the objects had been placed in the robot’s visual field the experimenter waited for the SOMs to settle. This corresponds to the three second pre-labeling pause at the beginning of each trial in Experiment 1. Then, the experimenter labeled the target object five times. The robot then individuated each object in its visual field by turning its head. Object representations in the color and shape SOMs were activated in response to the visual stimulus, which in turn spread activation to the label field and posture SOM, which then caused iCub to point at the corresponding object. After iCub made a selection and moved its arms and hands back to its baseline position, the experimenter ostensibly named the target object: the experimenter moved the target object away from the other objects, pointed to it and named it, for example, “This is the *cheem*!”

2) *Retention and generalization.* Immediately following the referent selection trials we presented iCub with four retention trials followed immediately by four generalization trials. The procedure for these trials was identical to the procedure for the referent selection trials except that the target object was labeled twice. As in Experiment 1, retention and generalization trials included no known objects, thus correct responding reflected the robot’s robust name-object associations [29]. Specifically, retention trials tested iCub’s memory of just-formed associations, and generalization trials tested whether these associations could be extended to new exemplars from the same object categories. As in previous child studies (e.g., [43, 44])

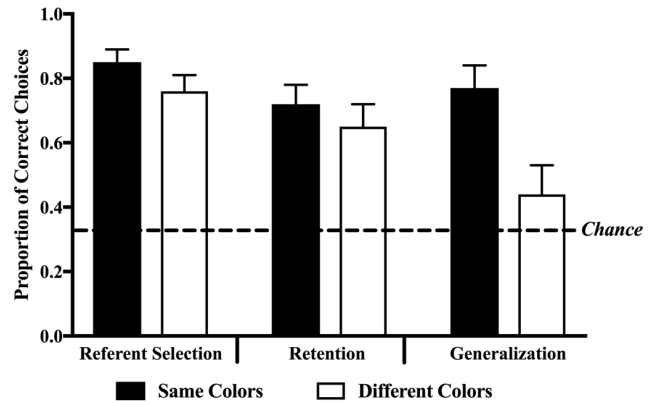


Fig 4. Data from the iCub simulations. Dark bars indicate the same colors condition, white bars indicate different colors condition. Dotted line indicates level of chance performance. Error bars represent one standard error of the mean. We do not include asterisks to indicate significance levels as these data are from simulations.

only the words that iCub correctly selected during the referent selection trials were included in the retention analyses and only words that iCub correctly retained were included in the generalization analyses.

C. Results and Discussion

Results are depicted in Figure 4. iCub selected target objects significantly more than expected by chance (.33) on novel name referent selection trials (all t -tests two-tailed; same colors: $M = .85$, $SE = .04$, $t(17) = 12.58$, $p < .001$, $d = 2.63$; different colors: $M = .76$, $SE = .05$, $t(17) = 9.18$, $p < .001$, $d = 2.16$) and performed equally well in each condition, $t(33.36) = 1.33$, $p = .19$, $d = .46$.

On retention trials the robot also selected target objects at levels greater than chance (same colors: $M = .72$, $SE = .06$, $t(17) = 7.33$, $p < .001$, $d = 1.51$; different colors: $M = .65$, $SE = .07$, $t(17) = 4.51$, $p < .001$, $d = 1.06$). Again, there was no difference in retention performance between conditions, $t(31.69) = 0.84$, $p = .41$, $d = .23$. Overall, then, iCub demonstrated the same pattern of behavior as the children in Experiment 1. Also note, iCub’s performance on the retention trials also replicates findings from previous studies of word learning using ERA and iCub [29, 55].

The critical test for the current simulations was iCub’s performance on generalization trials. The robot generalized novel names to their correct targets at above-chance levels in the same colors condition ($M = .77$, $SE = .07$, $t(17) = 6.14$, $p < .001$, $d = 1.20$). Importantly, performance in the different colors condition did not differ from chance ($M = .44$, $SE = .09$, $t(17) = 0.83$, $p = .42$, $d = 0.20$); further, performance in the same colors condition was significantly better than performance in the different colors condition ($t(33.70) = 3.98$, $p < .001$, $d = 1.37$). Overall, then, the iCub demonstrated the same pattern of behavior as the children in Experiment 1: only in the same colors condition was iCub able to generalize the novel names to new exemplars from the target categories.

IV. GENERAL DISCUSSION

The current project explores how reducing the problem space by manipulating task irrelevant information present during ambiguous naming events influences word learning. Children (Experiment 1) and iCub (Experiment 2) completed referent selection trials with either color constant or color variable sets of objects. Both children and iCub were able to associate the correct name with the original exemplars on the retention trials. However, only in the same colors condition were children and iCub able to extend the correct name to new, different colored, exemplars from the same object categories. Although children had large enough vocabularies to know that shape is the best indicator of object category membership (and hence object names), they continued to process color, which was irrelevant to the task. Overall, then, this suggests that reducing the local salience of redundant attributes facilitates deeper encoding of task relevant attributes, which facilitates word generalization.

Thus, we demonstrate that when the task is relatively simple with easily discriminable objects, as traditional, multi-colored referent selection trials are for 30-month-old children, additional capacity that is not being consumed by the main task can then be expended on processing task-irrelevant attributes or extraneous objects. In the current study, children begin encoding both the objects' shapes *and* colors. On generalization test trials the new exemplars only shared the same shapes but not colors with the original exemplars and no longer matched children's fragile memory representations for the given object categories. As a consequence of having encoded the original colors children's performance suffered on these trials (see also [59, 60]). This disruption in performance suggests that learning phases need to be challenging enough to require robust, attentional processing to the main to occur. When the initial referent selection task included objects that were more difficult to discriminate, as same color referent selection trials, the task was sufficiently challenging to enable more robust learning of the given object categories.

As such, the current findings are consistent with evidence from cognitive psychology on "desirable difficulties" [61]. Specifically, learning contexts that trigger encoding support robust learning [62]. By holding color constant, we made the disambiguation trials more difficult: children and iCub had to carefully attend to the target objects' shapes to encode how the target objects were different from the known competitors because color was no longer a difference. These trials were still relatively easy (everyone performed well above chance), but the added difficulty facilitated encoding of the objects' shapes, which ultimately led to better word generalization than the condition in which attentional capacity was not exhausted.

By 30-months of age most English-speaking children have learned sufficient nouns to know to extend object names on the basis of shape. In contrast, iCub's pre-trained vocabulary was substantially smaller than that of the children and likely did not contain enough object categories to learn the "natural statistics" that support the shape bias [63]. In addition, iCub only encountered one exemplar per category during the vocabulary pre-testing phase, which is also unlikely to support the development of a shape bias [64]. However, we reduced the problem space during the referent selection phase from presenting three shapes and three colors in the different colors

condition to only three shapes and one color in the same colors condition. This change in the input enabled iCub to encode objects' shapes sufficiently robustly to support word generalization. iCub was able to learn that shape was the defining feature for the object categories without already having learned a shape bias. Additional research is needed to better understand the relationship between the shape bias and word learning [but see 65] as well how directing children's and iCub's attention during ambiguous naming events can lead to a behavior compatible with a shape bias without the underlying vocabulary support.

V. CONCLUSION

Previous research demonstrates that the presence of competitor objects during ambiguous naming events hinders children's word learning. The current study is the first to explore whether extraneous *perceptual features* of competitor objects also influence word learning. Specifically, we demonstrate that manipulating the shared features between the extraneous and target materials can reduce the problem space during referent selection and improve word learning. As such, these findings present both practical implications for early years educators and speech therapists as well as guidance to designers of educational materials (see also [66]). Taken together, these findings illuminate the critical role that perceptual load plays in early word learning.

APPENDIX

Input SOMs were initialized with random connection weights in the same range as the real input objects. For example, color input is processed into 36 bins, which each represent a 10 degree section of HSV color space, containing the relative proportion of pixels from an object with colors in that section of HSV color space. Thus, during the initial training phase the color SOM is shaped by generating 36 random number sequences, which are then normalized. The SOMs were trained using standard equations 1 (SOM activity) & 2 (SOM learning rule; [56]):

$$(1) \quad \text{BMU} = \underset{i}{\operatorname{argmax}} \left(1 - \sqrt{2} (a_j - w_{ij}) \right).$$

Where the Best Matching Unit (BMU; i) is the unit whose weight vector w is closest to the current input vector a .

$$(2) \quad \Delta w_{ij} = \alpha \exp \left(-\frac{\text{dist}^2}{2\text{size}} \right) (a_j w_{ij}).$$

The weights of each unit j in the neighborhood of the BMU are then modified to move closer in Euclidean distance to the current input vector, with changes scaled according to the distance of that unit from the BMU (dist) in the SOM (i.e., not in terms of the input space) and neighborhood size (size).

As is typical of SOMs [66] the neighborhood size and learning rate (α) decrease monotonically until the neighborhood size is 1. This allows the network to settle in a stable state but also maintain plasticity for future use. Once the network settles both the neighborhood size and the learning rate of the SOM are fixed to allow learning to continue at a low rate.

The color and shape SOMs and the label field are fully connected via Hebbian-type links [67], which propagate activation as in equation 3 (IAC spreading activation; cf.[68]):

$$(3) \quad \text{net}_i = \sum w_{ij} a_j + \beta \text{BMU}.$$

The positive rule if $net_i > 0$:

$$(4) \quad \Delta a_i = (\max - a_i)net_i - \text{decay}(a_i - \text{rest}).$$

The negative rule if $net_i < 0$:

$$(5) \quad \Delta a_i = (a_i - \min)net_i - \text{decay}(a_i - \text{rest}).$$

Thus, net_i is either the sum of spreading activation or the sum of spreading activation *plus* external activation, if i happens to be the BMU of a SOM or a currently active word.

We used the standard Hebb-like learning rule in Equation 4:

$$(4) \quad \text{If } a_i > 0 \text{ OR } a_j > 0$$

$$\text{If } a_i a_j > 0 \quad \Delta v_{ij} = \lambda a_i a_j (1 - v_{ij})$$

$$\text{Else} \quad \Delta v_{ij} = \lambda a_i a_j (1 + v_{ij})$$

$$\text{Else} \quad \Delta v_{ij} = 0$$

This ensures that the strength of a weight (v) between SOMs increases if both units connected by this weight are positively active and reduces its strength if only one is positively active. This change is scaled according to the product of the units' activity and how close the weights are to 1 or -1, respectively, for positive and negative weight changes.

Finally, adaptive connections exist only between the SOMs and label field, while constant-valued (-0.8) inhibitory spreading activation connections exist within each SOM and within the label field.

Parameter values were as follows:

Learning Parameter value $\lambda = 0.005$.

External Input Bias (β) = 0.5; Max = 1; Min = -0.2.

Decay = 0.5; Rest = -0.01.

All other model parameters are the same as reported by Morse et al. [69]. The architecture itself differs in that it includes separate shape and color SOMs.

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